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RESEARCH

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Interlinkages across US sectoral returns: time-varying interconnectedness and hedging effectiveness

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Abstract

This study examines the time-varying asymmetric interlinkages between nine US sectoral returns from January 2020 to January 2023. To this end, we used the time-varying parameter vector autoregression (TVP-VAR) asymmetric connectedness approach of Adekoya et al. (Resour Policy 77:102728, 2022a, Resour Policy 78:102877, 2022b) and analyzed the time-varying transmitting/receiving roles of sectors, considering the positive and negative impacts of the spillovers. We further estimate negative spillovers networks at two burst times (the declaration of the COVID-19 pandemic by the World Health Organization on 11 March 2020 and the start of Russian-Ukrainian war on 24 February 2022, respectively). Moreover, we performed a portfolio backtesting analysis to determine the time-varying portfolio allocations and hedging the effectiveness of different portfolio construction techniques. Our results reveal that (i) the sectoral return series are strongly interconnected, and negative spillovers dominate the study period; (ii) US sectoral returns are more sensitive to negative shocks, particularly during the burst times; (iii) the overall, positive, and negative connectedness indices reached their maximums on March 16, 2020; (iv) the industry sector is the largest transmitter/recipient of return shocks on average; and (v) the minimum correlation and connectedness portfolio approaches robustly capture asymmetries. Our findings provide suggestions for investors, portfolio managers, and policymakers regarding optimal portfolio strategies and risk supervision.

Keywords: Asymmetric connectedness, SP500, Sectoral connectedness, Optimal portfolio strategies

JEL Classification: C32, C51, E43, G15

Introduction

The tight interconnectedness among global financial markets propels rapid risk transmission, rendering it crucial to understand how information is propagated. Moreover, the connectedness and co-movements between financial markets are prone to notably amplify around financial burst episodes (Diebold and Yilmaz 2014), thereby a comprehensive understanding of risk propagation and monitoring leads to a better establishment of policies, the regulatory framework for it, optimal asset allocations, and hedging effectiveness. In this context, an abundant and rich literature on stock market connectedness has proliferated over the last decade and progressed with the emergence of the COVID-19 pandemic (Youssef et al. 2021; Benlagha and El Omari 2022; Vidal-Llana et al. 2023). However, most of these studies have focused on stock market connectedness from a global perspective (i.e., between regions, continents, and states) and have not considered the asymmetric effects. This suggests that the literature on sectoral connectedness at the country level that considers asymmetric effects is still in its infancy.

Intuitively, discrepancies between positive and negative equity returns can occur in equity markets, and investors can be more sensitive to asymmetric returns. For example, hedgers and profit-maximizing agents can benefit more from negative sentiment under bullish/bearish market conditions (Beber and Brandt 2010). The ongoing COVID-19 pandemic sets an example of this, and strong and pervasive shock spillovers occur from hedge funds to financial assets, particularly for the future (Noori and Hitaj 2023). Although pioneering studies have reported the inherency of asymmetries in returns/volatilities (Christie 1982; French et al. 1987), only a few have examined static asymmetric return/volatility connectedness in financial markets (Baruník et al. 2016; Wang and Wu 2018; Iqbal et al. 2022; Mensi et al. 2021a, b). To fill this gap, our study delves into the time-varying asymmetric connectedness among sectoral returns at the country level.

An in-depth and accurate understanding of sectoral connectedness would provide valuable insights for portfolio managers, investors, and stakeholders in constructing portfolio allocations and making diversification and hedging decisions. In addition, a profit-maximizing agent does not process similar perceptions of positive and negative information, inducing a larger relative effect of negative sentiment spillovers than that of positive sentiment spillovers on financial markets (Mensi et al. 2021a, b). Therefore, a comprehensive understanding of time-varying asymmetric sectoral connectedness would help portfolio managers diversify portfolios in a timely and efficient manner, which, in turn, would strengthen the soundness of the financial system by reducing systemic risk.

As extensively reported by scholars, geopolitical/financial risks have prominently shaped the global economy (Sharif et al. 2020; Youssef et al. 2021; Tang et al. 2023) and have occasioned the intensification of connectedness among various asset classes. In this vein, abundant literature has augmented financial connectedness around financial/geopolitical bursts, such as the ongoing pandemic (Bouri et al. 2021; So et al. 2021; Costa et al. 2022; Antonakakis et al. 2023), the Russian-Ukrainian conflict (Adekoya et al. 2022a; Umar et al. 2022; Shahzad et al. 2023) and determined amplified interconnectedness among the assets. However, to the best of our knowledge, no study has examined the time-varying asymmetric connectedness among sectoral returns at the country level considering these two geopolitical upheavals and focusing on the hedging effectiveness of various portfolio construction methodologies. Our study contributes to the literature by examining the dynamic asymmetric sectoral connectedness of the US, which ranks as the largest world economy in terms of gross domestic product (GDP) and has been markedly influenced by the ongoing pandemic.

Recent studies have extensively examined intrasectoral connectedness in advanced economies, particularly in the US (Ahmad et al. 2021; Choi 2022; Hernandez et al. 2022). Understanding information transmission patterns in these economies is of paramount importance because they are a source of market contagion, especially during burst episodes (Boubaker et al. 2016; Apergis et al. 2019; Pino and Sharma 2019; Akhtaruzzaman et al. 2021; Choudhury and Daly 2021; Mensi et al. 2021a, b).

The US economy accounted for 24.7% of the global economy in 2022 in nominal terms,[1] with a stock market capitalization of $40,511 billion.[2] In addition, the US market is tightly connected to global financial markets through various channels, such as trade, commodities, derivatives, and forex rates, which propel rapid risk transmission from the US markets to the global financial markets. A comprehensive perception of interlinkages in the US stock market, particularly at the sectoral level, would enable policymakers to enact timely regulatory norms, especially if they know the asymmetric spillovers in each sector. Likewise, investors can better manage their portfolio decisions and hedging effectiveness if they know the time-varying asymmetric return spillovers at the sectoral level (Mensi et al. 2021a, b). This is the motivation for our study.

Despite the substance of sectoral connectedness, the literature does not address the dependencies across time-varying asymmetries and market conditions. Therefore, this study addresses the following questions: (i) what proportion of return shocks does each sector propagate to itself (intra-sector transmission) and to other sectors? (inter-sector transmission); (ii) which sectors (aggressive or defensive) act as net receivers or transmitters?; (ii) how does US sectoral asymmetric connectedness evolve over time?; (iv) on average, what are the optimal weights of sectoral returns under different portfolio construction scenarios and what is their hedging effectiveness when considering asymmetry?

To achieve this, we adopted the novel methodology of Adekoya et al. (2022b), which uses the TVP-VAR-based asymmetric connectedness approach in the spirit of the methodology of Antonakakis et al. (2020). We employed nine S&P 500 sectoral return indices in the analysis, with the data spanning from January 2, 2020 to January 26, 2023.

This study contributes to the existing literature in three ways. First, it examines the time-varying asymmetric connectedness among S&P 500 sectoral returns using a novel approach. By doing so, we not only focus on the dynamic nature of the asymmetric connectedness between sectors but also analyze the net transmission/recipient roles of sectors. Second, it investigates the asymmetric sectoral return connectedness for the US over the course of the COVID-19 pandemic by capturing well-known geopolitical/financial stress incidents. In turn, it provides insights into whether investors are more sensitive to asymmetric shocks. Finally, it investigates the optimal portfolio weights under different portfolio construction techniques and their hedging effectiveness by considering asymmetry.

The remainder of this paper is organized as follows. In section "Literature review" presents a literature review. In section "Data" presents the data and methodology used in the study. In section "Empirical results" presents and discusses the empirical results. In section "Time-varying portfolio analysis" presents the main findings and concludes.

[1] https://www.pwc.com/gx/en/research-insights/economy/global-economy-watch/projections.html.

[2] https://siblisresearch.com/data/us-stock-market-value/

Literature review

The growing pace of financial market integration and financial liberalization has precipitated expeditious information transmission, inducing a contagion impact. The interdependence between asset returns and volatilities is prone to augmenting market crashes and creating a stronger reaction to negative sentiment (Wu 2001). Thus, portfolio managers and financial investors need to accurately model their portfolio construction decisions and diversification policies. This requires a comprehensive understanding of the transmission between financial markets to hedge positions, particularly during turbulent times (Mensi et al. 2021a, b). This not only enhances portfolio managers' portfolio management strategies but also lessens the systemic/systematic risk of markets, which is crucial for policymakers to ensure financial soundness.

Systemic risk is associated with the potential failure of a company, event, or shock that can trigger the widespread collapse of the entire financial system. The notion of systemic risk highlights the importance of understanding and managing interdependencies and vulnerabilities within complex systems to prevent potential collapse. Nevertheless, understanding or encapsulating systemic risk using conventional methods is challenging. Therefore, the recent literature has focused on the prediction and/or measurement of systemic risk by employing engineered methods, including machine learning techniques. A detailed survey of this research line can be found in Kou et al. (2019).

Kou et al. (2021a) introduced a bankruptcy prediction model for small and medium-sized enterprises (SMEs) using transactional data and payment network-based variables under the scenario of no financial (accounting) data. Their results validate the forecasting ability and economic advantage of variables derived from transactional data. Likewise, Kou et al. (2021b) examined fintech-based investments in European banking services by employing a novel methodology that amalgamates interval type-2 (IT2) fuzzy decision-making trial and evaluation laboratory and IT2 fuzzy TOPSIS models. Payment and money transfer systems were determined to be the most important fintech investment alternatives based on their results.

Some scholars have used cluster algorithms to examine patterns in financial data or risks. Kou et al. (2016) introduced a multiple-criteria decision making (MCDM)-based approach to rank-clustering algorithms in financial risk analysis. Their findings highlight the efficacy of MCDM techniques in evaluating clustering algorithms. Similarly, Li et al. (2021) developed an integrated method for identifying clusters in financial data. Their results using 10 financial datasets showed the efficiency of the algorithm in identifying a reasonable number of clusters.

The growing integration of international equity markets, driven by globalization and financial liberalization, has engendered many studies on equity market connectedness. Scholars have utilized various econometric methods to compute interlinkages among stock markets, such as correlations (Virk and Javed; 2017; Wang et al. 2019; Ren et al. 2021), ARCH/GARCH models (Hung 2021; Hung et al. 2022; Zheng et al. 2022), copulas (Wen et al. 2019; Mandacı et al 2020; Zhang et al. 2022), wavelet analysis (Sharif et al. 2020; Younis et al. 2020; Karamti and Belhassine 2022), and VAR or TVP-VAR-based static/dynamic connectedness approach in the spirit of the Diebold–Yilmaz (DY) approach (Diebold and Yilmaz 2014; Maghyereh et al. 2016; Chow 2017; Youssef et al 2021; Chatziantoniou et al. 2022; Costa et al. 2022; Aharon et al. 2023). It is worth remarking that most of these studies have determined strengthening static/dynamic connectedness among equity markets with the emergence of financial/geopolitical bursts, and downturns.

However, most of the aforementioned connectedness studies have concentrated on return or volatility transmissions among global equity market indices, and only a limited number have examined the intra-sectorial connectedness for emerging/developed economies. Ahmad et al. (2021) examined connectedness among the US equity sectors and implied volatilities of oil, gold, and the Chicago Board Options Exchange Volatility Index (VIX) between April 2008 and March 2020 by employing time- and frequency-based connectedness approaches. The results of the study indicated that the spillovers of US sectoral equities amplified around the COVID-19 outbreak, and VIX is the largest transmitter of spillovers to the equity sectors, followed by the industry. Similarly, Choi (2020) analyzed volatility spillovers for the S&P 500 sectors during the COVID-19 pandemic by implementing the DY methodology. The findings suggested that the pandemic propelled a sudden increase in volatility spillovers, a large portion of which stemmed from the energy sector. Costa et al. (2022) examined volatility connectedness among 11 US sectoral indices between early 2013 and the end of 2020 using the DY approach. Their results showed that pairwise connectedness notably changed at the onset of the pandemic and that the industry sector was the largest net transmitter of shocks before and during the pandemic. Hernandez et al. (2022) studied the spillovers for US sectoral returns under low/high volatility regimes by performing the regime-switching autoregressive model and Granger causality test from May 2007 to February 2020. This study determined strengthening spillovers following the outbreak of the pandemic and the largest transmitter/recipient of shocks in the energy sector. Intra-sectoral connectedness studies are not limited only to the US, but they address emerging economies such as China (Wu et al. 2019; Zhang et al. 2020; Cui and Zou 2022), Turkey (Alkan and Çiçek 2020), and India (Chatziantoniou et al. 2022).

Despite asymmetries having long been tackled as a stylized fact in financial markets (Black 1976; Christie 1982; French et al. 1987) and investors' perception discrepancies against negative/positive news, studies on the asymmetric connectedness of returns or volatilities of sectoral equities are quite limited and still in their infancy. In this strand, Baruník et al. (2017) investigated asymmetric volatility spillovers among the seven most liquid US sectors in August 2004 and December 2011 and reported evidence of asymmetry for most US sectors. However, they found no evidence of the dominance of negative spillovers over positive spillovers. Chen et al. (2019) examined sectoral volatility connectedness in the Chinese stock market between July 2007 and June 2016 by employing the same approach as Baruník et al. (2017) and determined that bad volatility spillovers dominated the study episode. Likewise, Wen et al. (2019) examined the impact of retail investor sentiment on the Chinese stock market crash using firm-level data for 2007 and 2017. Their results indicated a negative association between retail investor attention and firm-level crash. Similarly, Mensi et al. (2021a, b) explored time-varying asymmetric spillovers between commodity and 10 sectors in the Chinese equity market between January 2005 and May 2020 using the DY approach. The results suggest that negative spillovers are larger relative to positive spillovers, and the industrial and consumer discretionary sectors are the largest transmitters and receivers of spillovers in the system.

Table 1 Summary of asymmetric connectedness studies

Study	Market (s)	Data period	Results
Baruník et al. (2017)	Seven most liquid US sectors	August 2004-December 2011	Evidence of asymmetry for US sectors
Chen et al. (2019)	Chinese stock market sectors	July 2007-June 2016	Domination of bad volatility
Mensi et al. (2021a, b)	Ten sectors in the Chinese equity market	January 2005- May 2020	Domination of bad volatility
Suleman et al. (2021)	Dow Jones Islamic Market Index (DJIM) and the Brent crude oil, gold, and silver markets	4 January 2010- 30 November 2020	Domination of bad volatility
Cao et al. (2022)	Fifteen financial variables from Chinese financial system and global financial markets	7 August 2015–30 September 2020	Domination of bad volatility
Mensi et al. (2022)	The spot prices of West Texas Intermediate crude oil and six major currencies	2 June 2011- 26 June 2021	Domination of bad volatility
Abdullah et al. (2023)	Halal tourism stocks, green stocks, cryptocurrency, gold, and oil	2018M12–2022M09	Time varying and highly event dependent asymmetry among variables
Alshater et al. (2023)	IT sectors of 13 countries	15 January 2016–24 June, 2022	Strong negative spillovers regardless of frequency

More recently, Adekoya et al. (2022a, b) examined time-varying asymmetric return spillovers among oil prices and Daw Jones Islamic stock indices between April 2013 and September 2021. They introduced a new time-varying asymmetric connectedness methodology based on the TVP-VAR connectedness approach of Antonakakis et al. (2020). Furthermore, they performed a dynamic portfolio exercise following Broadstock et al. (2022). Their findings revealed that except for the early stage of the pandemic, negative spillovers dominated the study episode, and the minimum connectedness portfolio analysis captured the asymmetry efficiently.

It is worth mentioning that recent studies have focused on the asymmetric connectedness among various financial assets (Suleman et al. 2021; Cao et al. 2022; Mensi et al. 2022; Abdullah et al. 2023; Alshater et al. 2023). Table 1 summarizes the aforementioned studies on asymmetric connectedness.

Data

We employed S&P 500 daily sectoral indices, namely Industrials (IND), Utilities (UTI), Energy (EN), Materials (MET), Consumer Staples (CS), Health Care (HC), Financials (FIN), Information Technology (IT), and Real Estate (RE).[3] We sourced data from the investing database, and the sample period ranged from January 2, 2020 to January 26, 2023.

We followed Adekoya et al. (2022a, b) and split the returns into positive and negative constituents as follows:

[3] The tickers for the S&P 500 sectoral indices are as follows, respectively: SPLRCI, SPLRCU, SPNY, SPLRCM, SPLRCS, SPSY, SPLRCT, and SPLRCREC.

Table 2 Descriptive statistics

	IND	UTI	EN	MAT	CS	HC	FIN	IT	RE
Mean	0.041	0.025	0.095	0.058	0.031	0.044	0.040	0.069	0.024
Variance	3.000***	2.893***	7.540***	3.158***	1.587***	1.881***	3.991***	4.095***	3.299***
Skewness	−0.239***	0.223**	−0.427***	−0.289***	−0.151*	−0.127	−0.111	−0.114	−0.810***
Kurtosis	10.142***	12.996***	8.053***	7.356***	12.758***	9.060***	10.525***	6.542***	12.722***
JB	3316.329***	5439.571***	2109.360***	1751.340***	5238.237***	2642.510***	3564.581***	1378.539***	5290.148***
ERS	−11.927***	−12.685***	−10.674***	−4.931***	−12.599***	−6.393***	−7.138***	−6.949***	−8.804***
Q(20)	108.676***	125.311***	41.445***	104.435***	130.736***	180.889***	127.063***	128.276***	98.334***
Q2(20)	893.502***	1181.253***	365.524***	764.381***	1098.245***	1140.915***	904.922***	630.893***	632.893***

Kendall correlations

	IND	UTI	EN	MAT	CS	HC	FIN	IT	RE
IND	1.000***	0.401***	0.454***	0.706***	0.478***	0.466***	0.697***	0.468***	0.493***
UTI	0.401***	1.000***	0.196***	0.361***	0.523***	0.415***	0.343***	0.287***	0.525***
EN	0.454***	0.196***	1.000***	0.443***	0.224***	0.222***	0.475***	0.227***	0.243***
MAT	0.706***	0.361***	0.443***	1.000***	0.457***	0.470***	0.634***	0.459***	0.459***
CS	0.478***	0.523***	0.224***	0.457***	1.000***	0.497***	0.427***	0.390***	0.500***
HC	0.466***	0.415***	0.222***	0.470***	0.497***	1.000***	0.427***	0.475***	0.477***
FIN	0.697***	0.343***	0.475***	0.634***	0.427***	0.427***	1.000***	0.419***	0.438***
IT	0.468***	0.287***	0.227***	0.459***	0.390***	0.475***	0.419***	1.000***	0.434***
RE	0.493***	0.525***	0.243***	0.459***	0.500***	0.477***	0.438***	0.434***	1.000***

***,**,*represent 1%, 5%, and 10% statistical significance levels, respectively. ERS: Stock et al.'s (1996) unit root test

$$R_t = \{0,\ \text{if} x_t < 0\ 1,\ \text{if} x_t \geq 0 \tag{1}$$

$$x_t^+ = R_t \cdot x_t \tag{2}$$

$$x_t^- = (1 - R_t) \cdot x_t \tag{3}$$

whereby, x_t^+, and x_t^- denote the positive and negative returns.

We employed the log daily returns of the S&P 500. Table 2 and Fig. 1 present the descriptive statistics of the price series and their plots, respectively.

We determined that, on average, all series provide positive returns. Moreover, EN is characterized by the highest return, followed by IT and MAT, while RE and UTI report the lowest average returns. As expected, and in line with the risk-return trade-off notion, EN reports the highest volatility. This finding also underpins the notable impact of the study period on the volatility of energy stemming from geopolitical stress incidents, such as the COVID-19 pandemic and the Russian-Ukrainian War (RUW). Except for UTI, all return series displayed a leftward-tailed distribution. All the series exhibited leptokurtic distributions, and the JB values indicate that they are abnormally distributed. Furthermore, all returns are significantly autocorrelated and display ARCH/GARCH errors. The correlation results indicate that the series are positively correlated.

Daily S&P 500 sectoral returns exhibited noteworthy spikes in March 2020, particularly around the proclamation of the COVID-19 pandemic. EN, HC, and FIN sharply fluctuated on November 9, 2020, owing to Pfizer's announcement that the vaccine

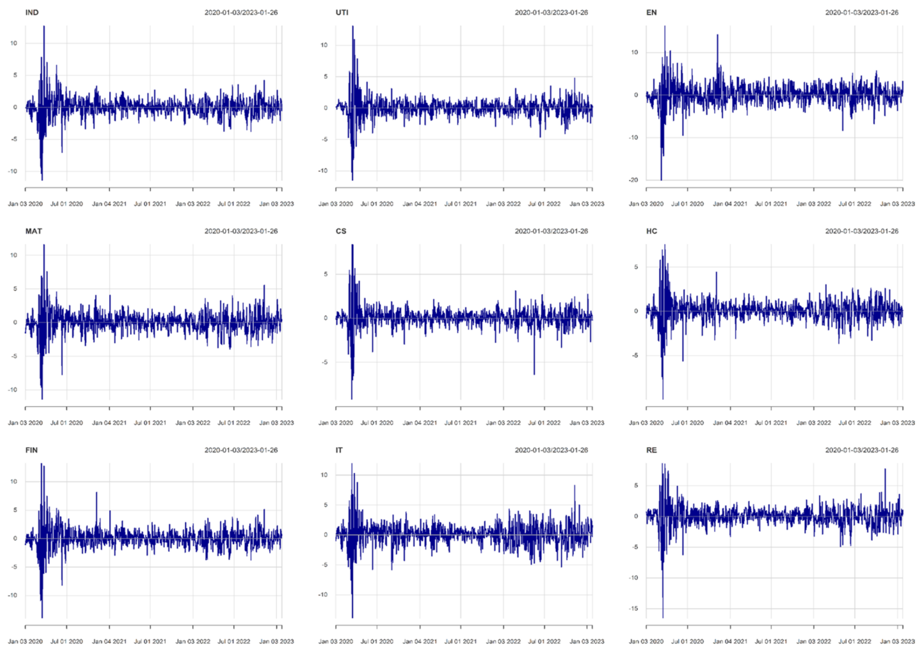

Fig. 1 S&P 500 sectoral returns

candidate was more than 90% effective against SARS-CoV-2.[4] Moreover, sharing a common trend, the return series remarkably elevated in November 2022, where the sectoral indices recorded monthly increases, owing to the expectation that the Federal Reserve Bank (FED) would slow its interest rate hikes.[5]

Methodology

Asymmetric connectedness

Adekoya et al. (2022a, b) present a TVP-VAR-based asymmetric connectedness methodology that uses positive and negative absolute returns. This methodology relies on the TVP-VAR connectedness method of Antonokakis et al. (2020), which is an extension of Diebold and Yilmaz's (2014) methodology.

Let us define the $TVP - VAR(p)$ as follows:

$$y_t = A_t x_{t-1} + \varepsilon_t \qquad \varepsilon_t|\Omega_{t-1} \sim N(0, \Sigma_t) \tag{4}$$

$$vec(A_t) = vec(A_{t-1}) + \gamma_t \qquad \gamma_t|\Omega_{t-1} \sim N(0, \Xi_t) \tag{5}$$

with

$$y_{t-1} = \left(y_{t-1} y_{t-2} \vdots y_{t-p} \right) \; A_{t'} = \left(A_{1t} A_{2t} \vdots A_{pt} \right) \tag{6}$$

[4] https://www.cnbc.com/2020/11/09/stock-market-live-updates-today.html.

[5] https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/s-p-500-gains-5-4-in-november-73353260

where Ω_{t-1} denotes all information available until $t-1$, and x_t and y_t denote $n\times 1$ and $np\times 1$ vectors. A_t and A_{it} are $n\times np$ and $np\times 1$ dimensional matrices, ε_t and γ_t are $n\times 1$ and $n^2p\times 1$ dimensional vectors, and Σ_t and Ξ_t are $n\times n$ and $np\times n^2p$ dimensional matrices, respectively.

The vector moving average (VMA) representation of y_t is provided as $\sum_{j=0}^{\infty}B_{jt}\mu_{t-j}$, where B_{jt} is the $n\times n$ dimensional matrix.

$GIRF\left(\Psi_{ij,t}(H)\right)$ is introduced as follows:

$$GIRF\left(H,\rho_{j,t},\Omega_{t-1}\right)=E\left(y_t+H|e_j=\rho_{j,t},\Omega_{t-1}\right)-E\left(y_{t+j}|\Omega_{t-1}\right) \tag{7}$$

$$\Psi_{j,t}(H)=\frac{B_{H,t}\Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}}\frac{\rho_{j,t}}{\sqrt{\Sigma_{jj,t}}}\quad \beta_{j,t}=\sqrt{\Sigma_{jj,t}} \tag{8}$$

$$\Psi_{j,t}(H)=\Sigma_{jj,t}^{-1/2}B_{H,t}\Sigma_t e_j \tag{9}$$

where e_j denotes an $n\times 1$ selection vector. $GFEVD\left(\widetilde{\Phi}_{ij,t}(H)\right)$ is estimated based on $\widetilde{\Phi}_{ij,t}(H)$ as follows:

$$\widetilde{\Phi}_{ij,t}(H)=\frac{\sum_{t=1}^{H-1}\Psi_{ij,t}^2}{\sum_{j=1}^{n}\sum_{t=1}^{H-1}\Psi_{ij,t}^2} \tag{10}$$

with $\sum_{j=1}^{n}\widetilde{\Phi}_{ij,t}(H)=1$, and $\sum_{i,j=1}^{n}\widetilde{\Phi}_{ij,t}(H)=n$.

The total connectedness index (TCI) is defined as

$$C_t(H)=\frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^{n}\widetilde{\Phi}_{ij,t}(H)}*100=\frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n}*100 \tag{11}$$

Overall directional connectedness to others is defined as

$$C_{i\rightarrow j,t}(H)=\frac{\sum_{j=1,i\neq j}^{n}\widetilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{n}\widetilde{\Phi}_{ji,t}(H)}*100 \tag{12}$$

Overall directional connectedness from others is defined as

$$C_{i\leftarrow j,t}(H)=\frac{\sum_{j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{\sum_{j=1}^{n}\widetilde{\Phi}_{ij,t}(H)}*100 \tag{13}$$

and net total directional connectedness as

$$C_{i,t}(H)=C_{i\rightarrow j,t}(H)-C_{i\leftarrow j,t}(H) \tag{14}$$

Chatziantoniou and Gabauer (2021) improve this connectedness measure, and adjusted the TCI as follows:

$$C_t(H)=\left(\frac{n}{n-1}\right)\frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n}=\frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n-1} \tag{15}$$

Dynamic portfolio approach

Following Broadstock et al. (2022), we employ multivariate portfolio construction methodologies and examine hedging effectiveness of them.

Minimum variance portfolio (MVP)

This approach aims to maximize the expected portfolio return while minimizing the portfolio risk. The MVP constitutes an optimal trade-off between risk and return (Markowitz, 1952). The portfolio allocations are calculated as:

$$w_t = \frac{\sum I}{I \sum_t^{-1} I} \tag{16}$$

Here, w_t is $m \times 1$ dimensional portfolio weight vector, I is an n-dimensional unit vector, and $\sum_t$ is an $n \times n$ dimensional conditional variance–covariance matrix.

Minimum correlation portfolio (MCP)

The correlation matrix is given as follows:

$$R_t = diag\left(\sum\nolimits_t\right)^{-0.5} H_t diag\left(\sum\nolimits_t\right)^{-0.5} \tag{17}$$

R_t is an $n \times n$ dimensional matrix. The portfolio weights are computed as:

$$w_{Rt} = \frac{R_t^{-1} I}{I R_t^{-1} I} \tag{18}$$

Minimum connectedness portfolio (MCoP)

The MCoP is introduced by the pairwise connectedness indices (Broadstock et al. 2022). The portfolio weights are calculated as below:

$$w_{Ct} = \frac{PCI_t^{-1} I}{I PCI_t^{-1} I} \tag{19}$$

where PCI_t is the pairwise connectedness index matrix.

Empirical results

Average interconnectedness findings

We present the average symmetric, positive, and negative connectedness results in Table 3.

It should be noted that the off-diagonal values in Table 3 indicate the shocks from the ith element to the jth element in the network. The symmetric connectedness results imply that S&P 500 sectoral returns have an average symmetric interlinkage level of 73.27%, indicating strong connectedness of sectoral returns. The largest transmitter/recipient of return shocks is IND (97.39, and 79.52, respectively), followed by MAT (90.12, and 78.34, respectively). This finding is consistent with that of Costa et al. (2022)

Table 3 Average connectedness results for S&P 500 sectoral returns

	IND	UTI	EN	MAT	CS	HC	FIN	IT	RE	FROM
IND	20.48	6	8.16	15.83	8.54	8.27	15.15	8.81	8.75	79.52
UTI	8.45	30.68	3.2	7.49	14.58	9.8	6.69	5.28	13.84	69.32
EN	13.14	3.65	37.79	12.52	4.2	4.19	14.85	4.8	4.86	62.21
MAT	16.72	5.63	8.08	21.66	8.17	8.61	14.32	8.78	8.04	78.34
CS	10.51	12.48	3.18	9.54	25.77	11.94	8.08	7.91	10.59	74.23
HC	9.99	8.5	3.07	9.92	12.04	26.36	8.42	11.39	10.3	73.64
FIN	16.73	5.23	10.25	15	7.21	7.65	22.77	7.59	7.57	77.23
IT	11.32	4.81	3.72	10.7	9	12.21	8.87	28.89	10.49	71.11
RE	10.52	11.74	3.68	9.13	10.65	10.22	8.26	9.62	26.17	73.83
TO	97.39	58.04	43.33	90.12	74.4	72.9	84.64	64.19	74.42	659.43
NET	17.87	− 11.28	− 18.88	11.78	0.17	− 0.74	7.41	− 6.93	0.6	TCI = 73.27
Positive										
	IND	**UTI**	**EN**	**MAT**	**CS**	**HC**	**FIN**	**IT**	**RE**	**FROM**
IND	22.65	6.43	7.11	16.32	7.42	7.62	15.86	8.48	8.13	77.35
UTI	8.25	31.29	2.59	7.59	14.19	9.71	6.6	5.9	13.89	68.71
EN	12.34	3.82	42	11.24	3.34	3.58	15.01	4.39	4.27	58
MAT	17.1	6.3	6.73	23.71	7.54	8.57	13.92	8.61	7.52	76.29
CS	9.39	13.07	2.35	8.96	29.37	11.4	7.19	7.75	10.52	70.63
HC	9.42	9.54	2.37	9.99	11.3	28.96	7.43	11.06	9.91	71.04
FIN	17.66	5.7	9.56	14.75	6.29	6.69	25.1	7.35	6.9	74.9
IT	10.68	5.58	2.86	10.47	7.93	11.92	8.33	32.44	9.8	67.56
RE	9.79	12.29	2.92	8.69	10.25	9.65	7.71	9.37	29.33	70.67
TO	94.64	62.72	36.47	88.01	68.27	69.12	82.05	62.92	70.94	635.15
NET	17.28	− 5.99	− 21.53	11.73	− 2.36	− 1.91	7.15	− 4.65	0.28	TCI = 70.57
Negative										
	IND	**UTI**	**EN**	**MAT**	**CS**	**HC**	**FIN**	**IT**	**RE**	**FROM**
IND	19.79	6.24	7.6	14.85	9.33	9.23	14.13	9.1	9.73	80.21
UTI	9.41	29.81	3.85	8.26	12.51	9.7	7.47	5.96	13.04	70.19
EN	12.2	3.95	36.62	12.18	5.43	5.32	12.83	5.4	6.06	63.38
MAT	16.02	5.82	8	21.33	8.37	9.3	13.82	8.8	8.54	78.67
CS	11.53	10.56	4.15	9.63	24.19	11.82	9.11	8.75	10.26	75.81
HC	10.99	7.93	4.14	10.45	11.34	24.06	10.04	10.57	10.49	75.94
FIN	15.5	5.48	8.78	14.16	8.15	9	21.57	8.44	8.9	78.43
IT	11.46	5.05	4.34	10.5	9.29	11.61	9.73	27.46	10.56	72.54
RE	11.89	10.11	4.76	9.75	9.7	9.89	9.82	9.74	24.34	75.66
TO	99	55.14	45.61	89.78	74.12	75.88	86.95	66.75	77.59	670.81
NET	18.78	− 15.05	− 17.76	11.11	− 1.69	− 0.06	8.52	− 5.79	1.93	TCI = 74.53

Results are estimated using the TVP-VAR model with lag 1 (BIC) and 20-step ahead forecast error variance decomposition (FEVD)

and underpins the prominent role of the industry sector over the study period. In addition, UTI, EN, HC, and IT are net recipients of shocks, while the remaining returns are net transmitters.

The rest of Table 2 presents the average connectedness findings for the positive/negative returns. Positive/negative spillovers are, on average, similar in sign and magnitude. It is worth remarking that the total connectedness index (TCI) for the negative

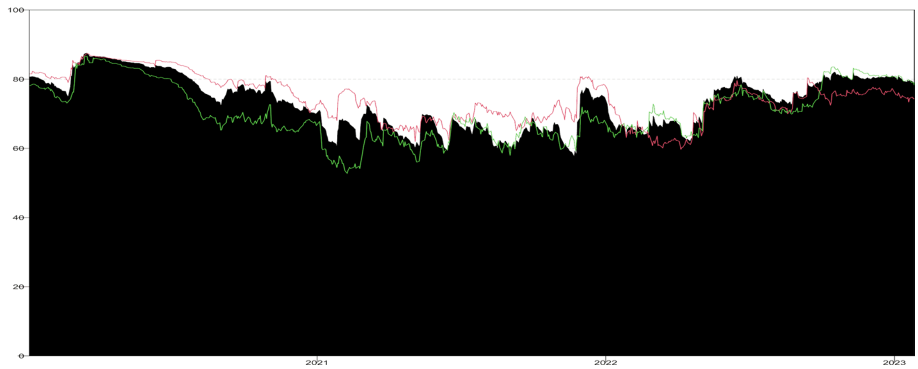

Fig. 2 Connectedness Indices. *Notes* Results are estimated by employing the TVP-VAR model with lag 1 (BIC) and a 20-step ahead FEVD

returns (74.53%) is higher than the TCI for the positive returns (70.57%). Regarding the net transmitting/receiving role of the returns, only CS becomes a net recipient of positive/negative return shocks, while the other nodes maintain their transmitting/receiving roles of shocks.

Time-varying asymmetric connectedness

To focus on the time-varying nature of asymmetric connectedness, we plot it in Fig. 2.[6]

Symmetric TCI oscillated between 57 and 88% over the study period and reached its maximum (87.56%) on March 16, 2020, shortly after the pandemic was announced. The index gradually plummeted until November 22, 2021 and hit its trough (57.59%). It moderately escalated afterward and hit approximately 79% by the end of January. Noticeably, the TCI sharply escalated from November 11, 2021 to December 7, 2021 and from April 17, 2022 to June, 15 2022, probably triggered by reaching the bull/bear market territories.[7] The TCIs for positive and negative returns displayed similar motifs and peaked on March 16, 2020 (86.62% and 87.45%, respectively). Moreover, the TCI for the negative returns dominated the study period, while that for positive returns was higher in March–April 2022 and on September 28, 2022 onward. The S&P 500 reached its lowest intraday level on September 28, 2022 since 2020.[8]

Dynamic net directional connectedness

We continue our analysis by focusing on the net directional connectedness of the S&P 500 sectoral returns to detect their transmitter/receiver roles over the study period. Figure 3 shows countries' net directional connectedness.[9]

IND, MAT, and FIN maintained their roles as net transmitters of return shocks throughout most of the episode. In line with our previous findings, positive return spillovers were stronger than negative return spillovers from November 2021 to January 2022

[6] The black shaded region represents the asymmetric total connectedness, and the green/red line exhibit the dynamics of TCIs for positive and negative returns, respectively.

[7] https://www.cnbc.com/2022/06/12/stock-market-news-open-to-close.html.

[8] https://www.bloomberg.com/news/articles/2022-09-28/asian-stocks-to-rally-as-boe-lifts-risk-sentiment-markets-wrap.

[9] Positive/negative values denote the transmitters/recipients in the system.

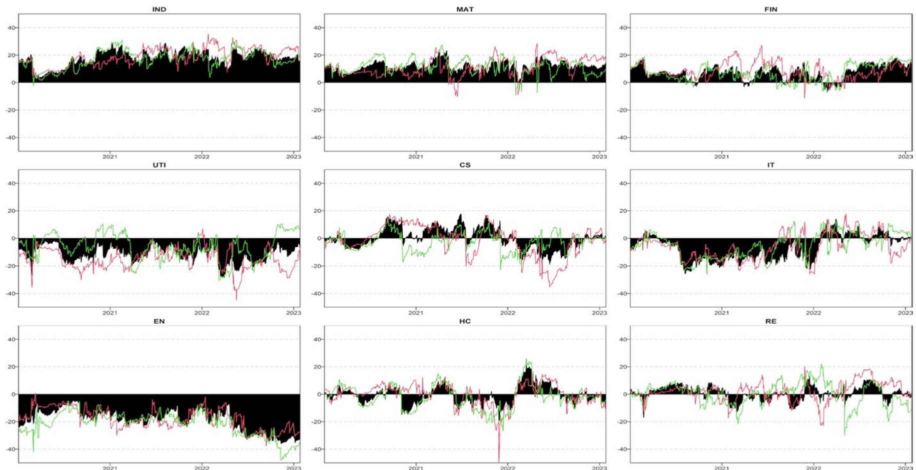

Fig. 3 Time-varying net directional connectedness. *Notes* Results are computed by employing the TVP-VAR model with lag 1 (BIC) and a 20-step ahead FEVD

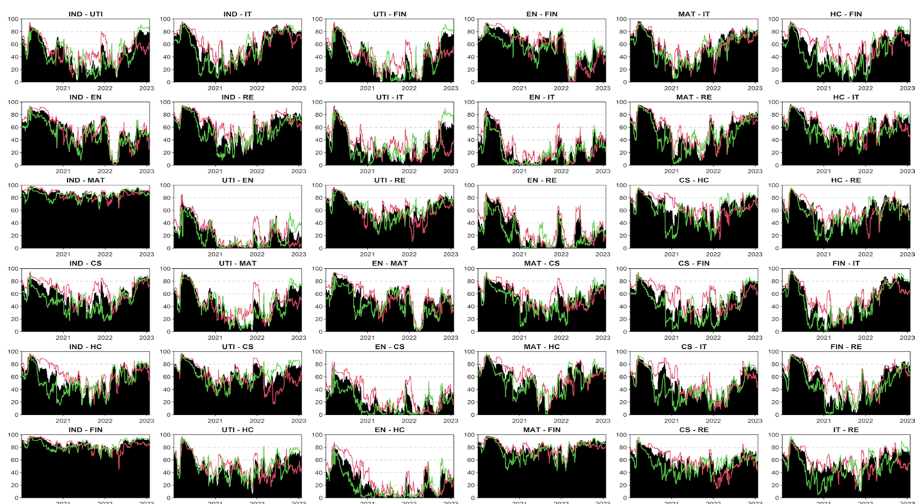

Fig. 4 Time-varying pairwise spillovers

because the market entered a bullish state. In contrast, UT, IT, and EN were net recipients of shocks over the study period—a finding consistent with Broadstock et al. (2022). Prominently, the discrepancies between positive and negative return spillovers started to surge in most sectors from late 2022. Furthermore, CS, HC, and RE were net transmitters/receivers of shocks depending on the period, while negative spillovers based on their returns dominated the study period.

Dynamic net pairwise connectedness

Next, we estimate the net pairwise connectedness among the sectoral returns and depict them in Fig. 4.

Several results based on the pairwise directional spillovers are noteworthy. First, pairwise asymmetric spillovers exhibited huge spikes in early 2020, coinciding with the proclamation of the pandemic. Second, negative pairwise spillovers dominated the study

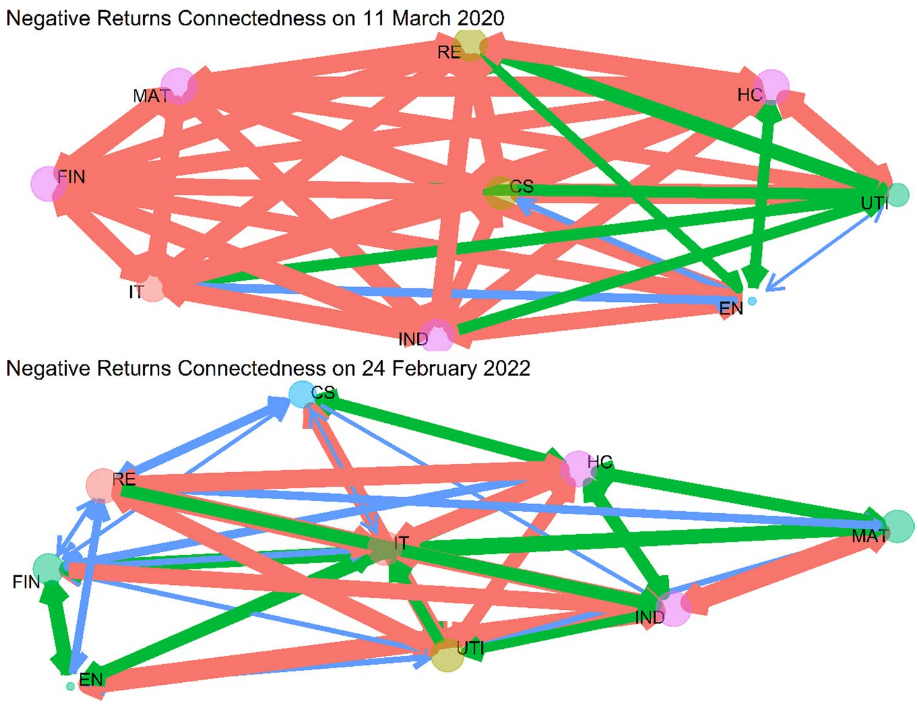

Fig. 5 Negative connectedness networks for the US sectoral returns

period. Third, pairwise spillovers were prone to escalation starting in early 2022. Fourth, negative and positive spillovers displayed similar patterns over most of the study period.

Network analysis

In this section, we perform a connectedness network analysis and estimate the interlinkages among sectoral returns at two burst times: the official declaration of the COVID-19 pandemic on March 11, 2020 and the start of the Russian invasion of Ukrainian (RIU) on February 24, 2022. Since negative spillovers dominate the study period, we compute networks of negative connectedness among the sectoral returns on March 11, 2020 and February 24, 2022 and depict them in Fig. 5.[10]

Negative connectedness networks indicate the following results. First, IND is the largest node transmitting negative return shocks in both networks.[11] This finding is consistent with the findings of Costa et al. (2022) and reveals the prominent role of the IND sector in transmitting negative shocks during burst periods. Second, the network estimated on the declaration of the pandemic is characterized by strong negative interlinkages among sectoral returns, underlying the deleterious impacts of the pandemic on US sectors. Third, the magnitudes of directional spillovers in the second network (estimated

[10] This figure shows the negative connectedness networks on March 11, 2020 and February 24, 2022, respectively. Arrows represent the direction of connections; the magnitude and color of the lines indicate the size of the connections, and the sizes of the vertices denote the total TO spillovers from that node.

[11] The sizes of nodes (IND, UTI, EN, MAT, CS, HC, FIN, IT, and RE) at the networks estimated on March 11, 2020 and February 24, 2022 are as follows: 81.13, 63.16, 84.98, 85.36, 83.71, 80.09, 85.99, 82.85, 70.13, and 27.82, 8.24, 36.02, 48.98, 48.048, 43.28, 40.24, 45.25, 41.36, respectively.

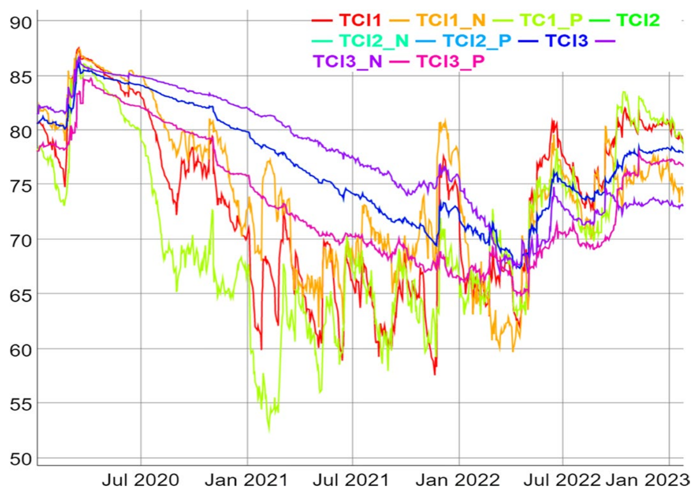

Fig. 6 TCIs for alternative model settings

on February 24, 2022) are stronger compared to the sizes of the connections in the first network.

Robustness test

Following Nham (2022), we conduct a diagnostic check for our asymmetric connectedness results by setting up different forecast horizons, decay factors (κ_1, and κ_2)[12] in our TVP-VAR asymmetric connectedness model and plot TCIs[13] estimated by them along with our original TCIs in Fig. 6.

TCIs estimated with alternative model parameters displayed similar patterns and peaks around the same time intervals during the study episode, demonstrating the accuracy of our results with alternative model settings.

Time-varying portfolio analysis

Dynamic portfolio analysis for US sectoral returns

We continue our analysis by focusing on the dynamic portfolio weights estimated using the MVP, MCP, and MCoP approaches. To this end, we compute the portfolio performance of each methodology by considering the overall returns (black lines) and positive/negative returns (green/red lines, respectively) and plot them in Fig. 7.

The trends in the time-varying portfolio weights in terms of overall, positive, and negative returns estimated by MVP, MCP, and MCoP exhibit similar patterns. Additionally, they provide evidence of asymmetry, particularly throughout the study period. Unsurprisingly, under the MVP method, the portfolio weights of HC and CS were higher than those of the other sectors in early 2020 probably due to the pandemic outbreak. The

[12] We selected forecast horizons (H = 10, and 30), and decay factors κ_1= 0.99 and κ_2 = 0.99 as alternative model settings.

[13] TC1, TCI_N, TCI_P: TCI estimations with lag 1, a 20-step ahead FEVD, decay factors κ_1= 0.99 and κ_2 = 0.96, TC11, TCI1_N, TCI1_P: TCI with lag 1, a 30-step ahead FEVD, and κ_1, κ_2= 0.99, and TC12 TCI2_N, and TCI2_P: TCI estimations with lag 1 (BIC), a 30-step ahead FEVD, and κ_1, κ_2= 0.99.

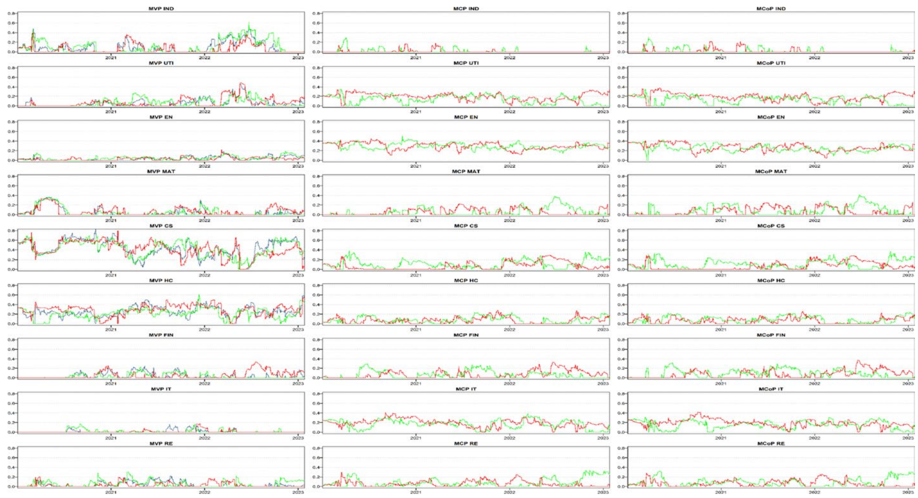

Fig. 7 Time-varying multivariate portfolio weights for the US sectoral returns

dynamic portfolio weights for sectoral returns under these three different techniques tended to increase considerably in the 2022–2023 period.

Next, we examine the hedging effectiveness of each portfolio construction methodology (MVP, MCP, and MCoP) and present them in Table 4, 5 and 6.

The results in Table 4 suggest that if, on average, we invest 9% in IND, 5% in UTI, 4% in EN, 5% in MAT, 43% in CS, 25% in HC, 4% in FIN, 1% in IT, and 4% in RE, then the proportions of volatilities in the portfolio will be statistically significant (except for CS), decreasing by 45% for IND, 43% for UTI, 78% for EN, 48% for MAT, -4% for CS, 12% for HC, 59% for FIN, 60% for IT, and 50% for RE. A negative CS value indicates that if we invest in this stock, the volatility of each stock in the portfolio would increase. As for the results for the positive and negative returns, it should be noted that the average weights and hedging effectiveness are quite similar and statistically significant, except for CS. Our results align with those of Broadstock et al. (2022) and suggest that positive and negative returns have similar weights on average.

Portfolio weights based on the MCP technique propose that if, on average, we invest in 0% in IND, 20% in UTI, 30% in EN, 5% in MAT, 7% in CS, 7% in HC, 6% in FIN, 20% in IT, and 5% in RE, then the proportion of volatilities in the portfolio will be statistically significant (except for IND, UTI, and MAT), lowered by 3% from IND, 0% from UTI, 61% from EN, 8% from MAT, -83% from CS, -54% from HC, 27% from FIN, 29% from IT, and 12% from RE. However, the values for IND, UTI, and MAT are not statistically significant. Moreover, the values for positive and negative returns have statistically significant contrasts and asymmetries. For example, the portfolio weights for the positive returns of IND, UTI, and MAT are statistically significant, while those for the negative returns are not. Furthermore, the weights suggest asymmetries in the magnitudes and signs between positive and negative returns.

The findings in Table 6 suggest that, on average, we invest 0% in IND, 19% in UTI, 26% in EN, 7% in MAT, 8% in CS, 8% in HC, 8% in FIN, 19% in IT, and 7% in RE; then the contribution volatility of each asset in the portfolio will be statistically significant (except for IND, UTI, and MAT), reduced by 7% from IND, 3% from UTI, 63% from

Table 4 MVP allocations for the US sectoral returns

	Mean	Standard deviation	5%	95%	Hedging effectiveness	*p*-value
IND	0.09	0.11	0.00	0.33	0.45	0.00
UTI	0.05	0.08	0.00	0.21	0.43	0.00
EN	0.04	0.04	0.00	0.11	0.78	0.00
MAT	0.05	0.09	0.00	0.30	0.48	0.00
CS	0.43	0.18	0.09	0.67	− 0.04	0.58
HC	0.25	0.11	0.09	0.43	0.12	0.07
FIN	0.04	0.06	0.00	0.17	0.59	0.00
IT	0.01	0.03	0.00	0.09	0.60	0.00
RE	0.04	0.05	0.00	0.15	0.50	0.00
	Mean	**Standard deviation**	**5%**	**95%**	**Hedging effectiveness**	***p*-value**
IND	0.11	0.13	0.00	0.39	0.43	0.00
UTI	0.06	0.08	0.00	0.23	0.45	0.00
EN	0.05	0.04	0.00	0.14	0.77	0.00
MAT	0.05	0.09	0.00	0.30	0.45	0.00
CS	0.43	0.16	0.14	0.64	− 0.03	0.69
HC	0.21	0.10	0.00	0.35	0.14	0.03
FIN	0.03	0.05	0.00	0.12	0.59	0.00
IT	0.02	0.03	0.00	0.10	0.58	0.00
RE	0.06	0.07	0.00	0.18	0.46	0.00
	Mean	**Standard deviation**	**5%**	**95%**	**Hedging effectiveness**	***p*-value**
IND	0.06	0.09	0.00	0.25	0.49	0.00
UTI	0.07	0.10	0.00	0.29	0.46	0.00
EN	0.03	0.03	0.00	0.09	0.79	0.00
MAT	0.07	0.08	0.00	0.26	0.49	0.00
CS	0.41	0.16	0.08	0.62	0.04	0.53
HC	0.29	0.11	0.06	0.44	0.13	0.05
FIN	0.05	0.08	0.00	0.22	0.60	0.00
IT	0.01	0.03	0.00	0.07	0.60	0.00
RE	0.03	0.05	0.00	0.14	0.56	0.00

EN, 12% from MAT, − 76% from CS, − 49% from HC, 30% from FIN, 32% from IT, and 15% from RE. Similar to the findings in Table 5, the portfolio weights and HE for IND and UTI are not statistically significant (while they are significant for MAT at the 10% significance level). Overall, the results obtained by the minimum connectedness approach are similar in magnitude and sign and indicate asymmetries between positive and negative returns.

The findings suggest the following policy recommendations. First, our findings on asymmetric sectoral connectedness can help investors and stakeholders implement portfolio diversification strategies and determine optimal portfolio allocations in a timely manner. Furthermore, the dominance of negative connectedness—particularly during heightened distress—and the discrepancies among asymmetric spillovers paraphrase an exemplary and robust risk-monitoring framework for policymakers to ensure the soundness of financial markets.

Table 5 MCP allocations for the US sectoral returns

	Mean	Standard deviation	5%	95%	Hedging effectiveness	*p*-value
IND	0.00	0.01	0.00	0.00	0.03	0.65
UTI	0.20	0.07	0.07	0.30	0.00	0.96
EN	0.30	0.05	0.22	0.38	0.61	0.00
MAT	0.05	0.05	0.00	0.16	0.08	0.24
CS	0.07	0.07	0.00	0.22	− 0.83	0.00
HC	0.07	0.06	0.00	0.17	− 0.54	0.00
FIN	0.06	0.07	0.00	0.20	0.27	0.00
IT	0.20	0.08	0.05	0.31	0.29	0.00
RE	0.05	0.05	0.00	0.16	0.12	0.08
Positive						
	Mean	**Standard deviation**	**5%**	**95%**	**Hedging effectiveness**	***p*-value**
IND	0.01	0.04	0.00	0.10	0.13	0.06
UTI	0.14	0.09	0.00	0.26	0.15	0.03
EN	0.29	0.06	0.21	0.41	0.64	0.00
MAT	0.06	0.08	0.00	0.23	0.16	0.02
CS	0.11	0.09	0.00	0.27	− 0.58	0.00
HC	0.07	0.07	0.00	0.19	− 0.31	0.00
FIN	0.06	0.08	0.00	0.23	0.37	0.00
IT	0.17	0.09	0.00	0.30	0.36	0.00
RE	0.08	0.09	0.00	0.28	0.17	0.01
Negative						
	Mean	**Standard deviation**	**5%**	**95%**	**Hedging effectiveness**	***p*-value**
IND	0.01	0.03	0.00	0.06	0.03	0.65
UTI	0.20	0.08	0.06	0.31	− 0.02	0.73
EN	0.30	0.07	0.16	0.40	0.60	0.00
MAT	0.05	0.06	0.00	0.18	0.04	0.54
CS	0.07	0.08	0.00	0.24	− 0.80	0.00
HC	0.07	0.06	0.00	0.18	− 0.63	0.00
FIN	0.07	0.08	0.00	0.24	0.24	0.00
IT	0.19	0.08	0.06	0.33	0.24	0.00
RE	0.06	0.06	0.00	0.18	0.17	0.01

Dynamic portfolio analysis for US sectoral returns and different asset classes

In the final phase of the study, we examine dynamic portfolio weights of the US sectoral returns along with different asset classes (crude oil-WTI, gold, Bitcoin-BTC)[14] estimated by MVP, MCP, and MCoP approaches. Since IND, MAT, and FIN are the largest transmitter of symmetric and asymmetric connectedness on average, we use these sectoral returns in the portfolio analysis. We compute the portfolio performances of each methodology considering the symmetric returns (black lines), and positive/negative returns (green/red lines, respectively), and plot them in Fig. 8.

[14] The data set has been collected from the Investing database.

Table 6 MCoP allocations for the US sectoral returns

	Mean	Standard deviation	5%	95%	Hedging effectiveness	*p*-value
IND	0.00	0.01	0.00	0.00	0.07	0.32
UTI	0.19	0.07	0.06	0.30	0.03	0.63
EN	0.26	0.06	0.18	0.37	0.63	0.00
MAT	0.07	0.07	0.00	0.21	0.12	0.09
CS	0.08	0.07	0.00	0.23	− 0.76	0.00
HC	0.07	0.06	0.00	0.17	− 0.49	0.00
FIN	0.08	0.08	0.00	0.22	0.30	0.00
IT	0.19	0.07	0.06	0.32	0.32	0.00
RE	0.07	0.06	0.00	0.17	0.15	0.02
Positive						
	Mean	**Standard deviation**	**5%**	**95%**	**Hedging effectiveness**	***p*-value**
IND	0.02	0.05	0.00	0.13	0.16	0.02
UTI	0.12	0.08	0.00	0.23	0.18	0.01
EN	0.25	0.07	0.15	0.37	0.66	0.00
MAT	0.08	0.10	0.00	0.26	0.19	0.00
CS	0.11	0.09	0.00	0.26	− 0.52	0.00
HC	0.08	0.07	0.00	0.20	− 0.27	0.00
FIN	0.09	0.08	0.00	0.23	0.39	0.00
IT	0.15	0.08	0.00	0.27	0.38	0.00
RE	0.09	0.08	0.00	0.27	0.20	0.00
Negative						
	Mean	**Standard deviation**	**5%**	**95%**	**Hedging effectiveness**	***p*-value**
IND	0.01	0.04	0.00	0.11	0.04	0.53
UTI	0.19	0.08	0.05	0.32	− 0.01	0.88
EN	0.27	0.08	0.14	0.39	0.61	0.00
MAT	0.06	0.08	0.00	0.21	0.06	0.42
CS	0.07	0.08	0.00	0.23	− 0.77	0.00
HC	0.07	0.06	0.00	0.17	− 0.61	0.00
FIN	0.07	0.08	0.00	0.25	0.25	0.00
IT	0.19	0.07	0.07	0.32	0.25	0.00
RE	0.06	0.07	0.00	0.21	0.18	0.01

The MVP results suggest that the dynamic optimal portfolio weights are allocated to WTI, gold, BTC, and GB, while the highest proportion is obtained for GB and followed by gold. However, the dynamic portfolio allocations of the US sectoral return are found to be zero throughout the episode and the optimal portfolio only consist of WTI, gold, BTC, and GB. On the other hand, dynamic portfolio weights estimated by the MCP and MCoP exhibit similar patterns which align with the findings of Broadstock et al. (2022). Additionally, the asymmetry is evident in both the MCP and the MCoP approaches.

Average portfolio allocations and the hedging effectiveness of each portfolio construction methodology (MVP, MCP, and MCoP, respectively) are given in Tables 7, 8, and 9, respectively.

Fig. 8 Time-varying multivariate portfolio weights for US sectoral returns and different asset classes

MVP allocations of assets indicate that if on average we invest in WTI 2%, in gold 7%, in BTC 1%, and in GB 8%, and the US sectoral returns 0%, then the proportions of volatilities in the portfolio will be statistically significant lowered by 97% from WTI, 54% from gold, 97% from BTC, and 100% in US sectoral returns. However, if we invest in GB then the volatility of each stock in the portfolio would increase. The results for the positive and negative returns are very similar to the symmetric results and statistically significant.

The MCP and MCoP techniques suggest more diversified portfolios. Moreover, the results are statistically significant, and negative HE for some asset classes indicates that if we invest in these assets then the volatility of each stock in the portfolio would increase. Corroborating our previous results and different than the MVP, the asymmetry is evident in the MCP and MCoP approaches.

Conclusion

In this work, we examined asymmetric time-varying connectedness between nine S&P 500 sectoral returns between 2020:1 and 2023:1. To this end, we implemented a newly engineered approach—asymmetric TVP-VAR connectedness—and focused on the time-varying transmitting/receiving roles of S&P 500 sectoral returns by considering the asymmetric (positive/negative) impacts of spillovers. Furthermore, we performed a portfolio backtesting analysis to detect the hedging effectiveness of different portfolio construction techniques (MVP, MCP, and MCoP) in the presence of asymmetry.

The time-varying asymmetric connectedness results suggest that the sectoral return indices are strongly interconnected on average, and connectedness based on negative returns dominates the study period. This finding underlines that S&P 500 sectoral returns are more sensitive to negative shocks, particularly during crisis episodes, which is in line with previous studies (Baruník et al. 2017; Adekoya et al. 2022a, b). Moreover, the industrial sector is the largest transmitter/recipient of overall positive and negative return shocks.

Table 7 MVP allocations for the US sectoral returns and different asset classes

	Mean	**Standard deviation**	**Hedging effectiveness**	***p*-value**
IND	0.00041	0.0007	0.47	0.00
UTI	0.00010	0.0003	0.41	0.00
EN	0.00010	0.0002	0.75	0.00
MAT	0.00030	0.0006	0.42	0.00
CS	0.00047	0.0006	0.32	0.00
HC	0.00058	0.0006	0.18	0.00
FIN	0.00098	0.0008	0.63	0.00
IT	0.00005	0.0002	0.65	0.00
RE	0.00014	0.0003	0.55	0.00
WTI	0.02385	0.0228	0.62	0.00
GOLD	0.16535	0.0656	0.83	0.00
BTC	0.00563	0.0081	0.57	0.00
GB	0.80222	0.0777	− 0.77	0.00
	Mean	**Standard deviation**	**Hedging effectiveness**	***p*-value**
IND	0.00029	0.00049	0.43	0.00
UTI	0.00011	0.00024	0.45	0.00
EN	0.00006	0.00012	0.77	0.00
MAT	0.00021	0.00044	0.45	0.00
CS	0.00037	0.00049	− 0.03	0.69
HC	0.00026	0.00033	0.14	0.03
FIN	0.00065	0.00071	0.59	0.00
IT	0.00009	0.00026	0.58	0.00
RE	0.00011	0.00022	0.46	0.00
WTI	0.01808	0.02374	0.55	0.00
GOLD	0.10930	0.05505	0.62	0.00
BTC	0.00513	0.00651	0.83	0.00
GB	0.86534	0.05904	0.57	0.00
	Mean	**Standard deviation**	**Hedging effectiveness**	***p*-value**
IND	0.00	0.00	1.00	0.00
UTI	0.00	0.00	1.00	0.00
EN	0.00	0.00	1.00	0.00
MAT	0.00	0.00	1.00	0.00
CS	0.00	0.00	1.00	0.00
HC	0.00	0.00	1.00	0.00
FIN	0.00	0.00	1.00	0.00
IT	0.00	0.00	1.00	0.00
RE	0.00	0.00	1.00	0.00
WTI	0.02	0.02	0.96	0.00
GOLD	0.07	0.09	0.49	0.00
BTC	0.01	0.01	0.97	0.00
GB	0.90	0.11	− 3.29	0.00

Time-varying connectedness indices exhibited similar patterns throughout the study episode and hit their apex on March 16, 2020, shortly after the pandemic was officially declared. This result points to the noteworthy impact of the COVID-19 pandemic on the overall and asymmetric connectedness of S&P 500 sectoral returns,

Table 8 MCP allocations for the US sectoral returns and different asset classes

	Mean	Standard deviation	5%	95%	Hedging effectiveness	*p*-value
IND	0.03	0.06	0.00	0.17	0.65	0.00
UTI	0.11	0.07	0.00	0.23	0.63	0.00
EN	0.07	0.07	0.00	0.21	0.87	0.00
MAT	0.04	0.06	0.00	0.18	0.67	0.00
CS	0.06	0.07	0.00	0.20	0.33	0.00
HC	0.06	0.06	0.00	0.17	0.43	0.00
FIN	0.09	0.09	0.00	0.26	0.74	0.00
IT	0.07	0.06	0.00	0.18	0.74	0.00
RE	0.04	0.05	0.00	0.14	0.69	0.00
WTI	0.10	0.05	0.00	0.18	0.62	0.00
GOLD	0.10	0.05	0.00	0.18	0.83	0.00
BTC	0.11	0.04	0.04	0.17	0.57	0.00
GB	0.11	0.05	0.02	0.18	– 0.77	0.00
Positive						
	Mean	**Standard deviation**	**5%**	**95%**	**Hedging effectiveness**	***p*-value**
IND	0.05	0.08	0.00	0.23	0.59	0.00
UTI	0.06	0.07	0.00	0.19	0.58	0.00
EN	0.08	0.07	0.00	0.21	0.84	0.00
MAT	0.02	0.05	0.00	0.17	0.60	0.00
CS	0.08	0.07	0.00	0.21	0.25	0.00
HC	0.06	0.06	0.00	0.17	0.36	0.00
FIN	0.08	0.08	0.00	0.21	0.70	0.00
IT	0.06	0.07	0.00	0.20	0.70	0.00
RE	0.04	0.06	0.00	0.15	0.60	0.00
WTI	0.10	0.06	0.00	0.19	− 0.67	0.00
GOLD	0.12	0.05	0.00	0.21	1.04	0.00
BTC	0.11	0.05	0.02	0.20	− 0.74	0.00
GB	0.14	0.06	0.02	0.22	− 1.08	0.00
Negative						
	Mean	**Standard deviation**	**5%**	**95%**	**Hedging effectiveness**	***p*-value**
IND	0.05	0.08	0.00	0.24	0.64	0.00
UTI	0.07	0.07	0.00	0.20	0.62	0.00
EN	0.08	0.07	0.00	0.20	0.86	0.00
MAT	0.02	0.04	0.00	0.10	0.65	0.00
CS	0.05	0.07	0.00	0.19	0.30	0.00
HC	0.09	0.07	0.00	0.23	0.39	0.00
FIN	0.07	0.08	0.00	0.22	0.72	0.00
IT	0.05	0.07	0.00	0.17	0.71	0.00
RE	0.03	0.05	0.00	0.13	0.69	0.00
WTI	0.11	0.06	0.02	0.22	− 0.63	0.00
GOLD	0.14	0.05	0.03	0.20	0.88	0.00
BTC	0.12	0.05	0.02	0.19	− 0.54	0.00
GB	0.13	0.06	0.02	0.23	− 0.74	0.00

Table 9 MCoP allocations for the US sectoral returns and different asset classes

	Mean	**Standard deviation**	**5%**	**95%**	**Hedging effectiveness**	***p*-value**
IND	0.03	0.06	0.00	0.17	0.65	0.00
UTI	0.11	0.07	0.00	0.23	0.63	0.00
EN	0.07	0.07	0.00	0.21	0.87	0.00
MAT	0.04	0.06	0.00	0.18	0.67	0.00
CS	0.06	0.07	0.00	0.20	0.33	0.00
HC	0.06	0.06	0.00	0.17	0.43	0.00
FIN	0.09	0.09	0.00	0.26	0.74	0.00
IT	0.07	0.06	0.00	0.18	0.74	0.00
RE	0.04	0.05	0.00	0.14	0.69	0.00
WTI	0.10	0.05	0.00	0.18	− 0.62	0.00
GOLD	0.10	0.05	0.00	0.18	0.83	0.00
BTC	0.11	0.04	0.04	0.17	0.57	0.00
GB	0.11	0.05	0.02	0.18	− 0.77	0.00
Positive						
	Mean	**Standard deviation**	**5%**	**95%**	**Hedging effectiveness**	***p*-value**
IND	0.03	0.07	0.00	0.17	0.66	0.00
UTI	0.07	0.06	0.00	0.18	0.65	0.00
EN	0.09	0.06	0.00	0.19	0.86	0.00
MAT	0.03	0.05	0.00	0.15	0.67	0.00
CS	0.07	0.07	0.00	0.22	0.37	0.00
HC	0.07	0.05	0.00	0.15	0.47	0.00
FIN	0.08	0.07	0.00	0.21	0.75	0.00
IT	0.07	0.07	0.00	0.20	0.75	0.00
RE	0.06	0.05	0.00	0.17	0.67	0.00
WTI	0.08	0.05	0.00	0.16	− 0.56	0.00
GOLD	0.11	0.04	0.00	0.16	− 0.86	0.00
BTC	0.12	0.04	0.05	0.17	− 0.62	0.00
GB	0.11	0.04	0.03	0.17	− 0.89	0.00
Negative						
	Mean	**Standard deviation**	**5%**	**95%**	**Hedging effectiveness**	***p*-value**
IND	0.04	0.07	0.00	0.20	0.64	0.00
UTI	0.12	0.08	0.00	0.27	0.62	0.00
EN	0.09	0.07	0.00	0.23	0.86	0.00
MAT	0.04	0.06	0.00	0.17	0.65	0.00
CS	0.05	0.06	0.00	0.18	0.30	0.00
HC	0.08	0.08	0.00	0.23	0.39	0.00
FIN	0.07	0.08	0.00	0.22	0.72	0.00
IT	0.09	0.07	0.00	0.20	0.72	0.00
RE	0.03	0.05	0.00	0.14	0.69	0.00
WTI	0.09	0.05	0.01	0.16	− 0.63	0.00
GOLD	0.10	0.05	0.02	0.18	− 0.87	0.00
BTC	0.11	0.04	0.04	0.17	− 0.53	0.00
GB	0.10	0.04	0.03	0.17	− 0.74	0.00

which is consistent with the findings of previous studies (Bouri et al. 2021; So et al. 2021; Bossman et al. 2022; Umar et al. 2022). Moreover, TCIs experienced noteworthy surges in November–December 2021 and April–June 2022, which also coincided with bullish/bearish market episodes.

In line with our average connectedness results, time-varying pairwise asymmetric spillovers indicate the dominance of negative spillovers over the study period, suggesting that investors and hedgers are more reactive to negative news. Moreover, we found that the industry, utilities, and energy sectors were mainly net receivers of return shocks, while sectors such as consumer staples, health care, and real estate shifted between net recipients and net transmitters over the course of the study period. Moreover, this asymmetry has become more evident since late 2022.

Additionally, we estimate networks of negative interlinkages among sectoral returns at two burst times (declaration of the pandemic and the RIU). Our network connectedness results indicate that IND is the largest node in propagating shocks in both networks and the COVID-19 network is featured by tighter interdependencies between sectoral returns compared to the network estimated for RIU. The TCIs computed with alternative model parameters exhibit similar motifs and intensify/alleviate around time intervals, indicating the robustness of our results with alternative model settings.

In the final stage of the study, we investigated the hedging effectiveness of different portfolio construction approaches and dynamic portfolio weights considering the asymmetric effects. The minimum variance portfolio approach didn't suggest a sharp statistically significant differences and asymmetry, while the other two methodologies (the MCP, and MCoP) provided similar results in terms of signs and magnitude of findings and reported evidence for asymmetry.

Furthermore, we compute dynamic optimal portfolio weights and hedging effectiveness for different asset classes (WTI, gold, BTC, and iShares USD Green Bond ETF) along with the US sectoral returns. Our findings propose more diversified portfolios the MCP and MCoP techniques and report the asymmetry for the MCP and MCoP techniques.

The findings of this study suggest the following policy recommendations. First, our finding in terms of asymmetric sectoral connectedness can help investors and stakeholders in performing their portfolio diversification strategies and determining optimal portfolio allocations in a timely manner. Furthermore, the dominance of negative connectedness particularly over the course of heightened distress, and the discrepancies among the asymmetric spillovers paraphrase an exemplary and robust risk monitoring framework for policymakers to ensure the soundness of financial markets.

Abbreviations

TVP-VAR	Time-varying parameter vector autoregression
TCI	Total connectedness index
DY	Diebold–Yilmaz
GDP	Gross domestic product
IND	Industrials
UTI	Utilities
EN	Energy
MET	Materials
CS	Consumer staples
HC	Health care
FIN	Financials

IT	Information technology
RE	Real estate

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Conceptualization, methodology, data analysis, original draft writing were conducted by the corresponding author. The author read and approved the paper.

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Declarations

Competing interests
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